Ontologically supported case-based reasoning for decision making in humanitarian response processes

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Abstract

The advantages and disadvantages of Case-Based Reasoning modifications and the possibilities of their application to improve the efficiency of decision-making in humanitarian response are analyzed. The development of Case-Based Reasoning is proposed through the ontological representation of cases and the introduction of semantic proximity measures, which allows taking into account the conceptual and semantic relationships between the concepts of the subject area to find solutions in conditions of incomplete information. The modified Case-Based Reasoning consists of three stages. The first stage involves extracting the ontological case that is closest to the parameters of the current situation by choosing the shortest path between the vertices of the taxonomy. The second stage involves the adaptation and development of the selected ontology, taking into account territorial, essential and performance attributes. At the third stage, the resulting ontology is enriched with new knowledge using ontology alignment and merging methods. The result of the modified Case-Based Reasoning is an enriched ontological case containing a solution for the current situation. An experimental verification of the modified Case-Based Reasoning is carried out on the initial data set. It is shown that the use of the ontological representation of cases and ontology enrichment procedures can improve the quality of classification compared to the classical parametric representation of cases by 5 %.

Keywords

humanitarian response, knowledge-oriented model, Case-Based Reasoning, ontology, Decision Support Systems

1. First level sectioning

Since the beginning of the 21st century, society has faced many challenges, such as armed conflicts, powerful earthquakes, industrial disasters, and natural disasters. The population in emergency affected zones needs humanitarian assistance to provide the necessary means

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of subsistence, such as housing, food and non-food products, utilities, and provision of rights to healthcare, education, social protection, etc. According to estimates [1], in 2024, 14.6 million Ukrainian citizens is in need of humanitarian assistance.

Planning and implementation of such assistance is a complex multi-stage process that takes place under tight time constraints and uncertainty. An important objective is to develop and implement Decision Support Systems (DSS) that support all stages of decision-making as part of analytical modelling of the population's needs for humanitarian assistance. Such systems do not produce decisions; their purpose is to interact between data, processing procedures, decision-making models and a responsible person to provide auxiliary information in solving unstructured or poorly structured tasks.

The use of a DSS based on knowledge-based data models will improve the quality of decision-making under conditions of uncertainty by using previous experience in solving similar problems. To process large amounts of information and respond promptly to the needs of the population of disaster-affected areas, a DSS based on a formalized knowledge representation and simple inference procedures is needed. The central element of such a system could be a case database containing information on previous experience of providing humanitarian assistance in various situations and procedures for selecting solutions similar to the current situation with the possibility of their adaptation.

The accumulated experience is usually represented in the form of cases that have a different structure and are stored in different formats. These can be ontologies built by different experts, or case databases represented in parametric form, decision trees, graph models, etc. When identifying a new situation, especially under conditions of uncertainty, it is necessary to analyze the set of available representations and select those cases that best fit the current problem according to a certain criterion. The complexity of choosing such a criterion is determined by the uniqueness of situations arising in humanitarian response, unpredictable developments in the war zone or natural or industrial disasters, uncertainty of goals and objectives, time, resource and assistance delivery limitations, the need to coordinate the actions of several actors, etc.

The purpose of the study is to develop knowledge-based methods of data presentation and analysis for effective decision-making in humanitarian response. The study aims to solve the following tasks: to identify the features of decision-making in humanitarian response and the functions of DSS; to extend the Case-Based Reasoning method with an ontological component in order to enrich previous experience with conceptual concepts of the subject area and the links between them; to determine the procedures for extracting, adapting and enriching ontological cases.

2. Literature review

An assessment of research in the field of humanitarian response has shown that most publications deal with humanitarian assistance in the context of decision-making in the prevention and response to natural and industrial disasters and armed conflicts. In recent decades, the number of works devoted to this topic has been growing steadily. The general trend is to identify the need to move from individual unsystematic solutions to "the formation of a common software environment for peacekeeping engineering" [2] to comprehensively address emerging problems. Humanitarian response programs are an essential part of peacekeeping engineering, so they require more in-depth research.

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To systematize knowledge in this subject area, Case-Based Reasoning (CBR) [3] is used, which allows accumulating experience about decisions made and reusing it in the future without involving complex procedures for extracting knowledge and interviewing experts.

The CBR is adjusted to the specifics of the tasks of the subject area. In [4], a modification of the CBR is proposed to support decision-making in humanitarian response, which takes into account the time factor. Temporal cases allow reflecting the dynamics of humanitarian response processes and present the current situation as a result of previous decisions, but they complicate the stage of case adaptation in cases of incomplete information.

The combination of classical CBR with an ontological approach extends the capabilities of Case-Based Reasoning by taking into account the conceptual concepts of the subject area, such as objects, attributes and logical relationships between objects. The use of ontologies makes it easier to integrate, search and reuse information. However, the procedures of the hybrid method significantly depend on the specifics of a particular subject area. In [5], the problems of representing subject matter knowledge for the application of CBR and Rule-Based Reasoning are considered. The use of ontologies can improve the quality of decisions by using a dual source of knowledge: the subject area and historical cases.

The combination of ontological representation and CBR is adapted to predict the consequences of disasters [6] and failures at engineering facilities [7, 8]. An approach based on controlling disaster preparedness errors is proposed in [6]. CBR is based on a cause-and-effect diagram, which is represented as an ontological model of fault control. Based on a structured scenario, a multi-phase search for a scenario similar to the current situation is presented.

An approach to decision-making for managing construction safety risks in the example of the metro, in which the reasoning process is improved by integrating a similarity algorithm and a correlation algorithm on ontologies, is considered in [7]. Obtaining knowledge from multiple sources of information helps to avoid missing important correlated information. In [8], the extension of CBR with ontologies is used to respond to the risk of hydrological cascade disasters. The method consists of four stages: filtering, deduction, copying, and adaptation of cases.

An approach to knowledge representation through situation identification is proposed in [9]. Non-monotonic logic and semantic web technologies are used to formalize and understand the situation. A hybrid top-down and bottom-up reasoning method is combined with CBR and inference rules to provide decision support in the field of man-made disasters.

Decision support in responding to the consequences of various disasters is considered in [10-13]. In [10], a hybrid CBR is proposed that uses an organized semantic model of knowledge representation designed to estimate the number of resources that will be deployed in the event of an emergency. The logical inference algorithm used improves the accuracy of recommendations in emergency situations.

The dual scenario model, which combines CBR with an ontology, is used to identify needs for international medical assistance [11]. The use of two types of cases, the first describing the disaster itself and the second a regional scenario describing the local health and medical services, allows for effective decision-making information based on past experience.

The problems of uncertainty and lack of information in decision-making are solved by extending the ontological approach with fuzzy logic. In [14], it is proposed to use fuzzy logic in the case when prior knowledge is not enough to form cases. The ontology-based decision-making model simulates the driver's behavioral decision-making process by displaying the "scene object – movement" relationship. This type of model allows storing driver knowledge from rules, cases to driving actions. The issues of categorization based on ontology and fuzzy logic using machine learning are discussed in [15]. The authors show that the effectiveness of the hybrid method is higher than the traditional CBR.

In [16], it is proposed to use a combination of CBR and ontological representation and fuzzy inference to detect and prevent natural disasters. The method takes into account the dynamics of objects in nature and the particularities of sensors that perceive images. The combination of ontologies and fuzzy logic methods is also successfully used in medical diagnostics [17]. Ontological semantic reasoning based on fuzzy inference improves the process of evaluating rules in terms of interpretability, dynamism, and intelligence.

Based on the analysis, it can be concluded that adapting the CBR method to the specifics of the subject area can improve the efficiency of decision-making. However, the determination of the degree of closeness of cases and the processes of their adaptation to the current situation remain uncertain.

3. Decision support system in humanitarian response

Humanitarian response can be defined as an open and dynamic subject area. In addition to analytical dependencies between parameters (for example, the number of people determines the amount of assistance needed), it can be distinguished by more complex relationships due to semantic, linguistic and predicative relations between the main concepts. Considering the specifics of decision-making in humanitarian response. The general steps of decision-making in a given subject area are shown in Figure 1,

It is important to consider that response processes are cyclical, and many scenarios can be repeated and adapted to new conditions or challenges. Identifying the situation at the analysis stage is key to determining the subsequent humanitarian response plan. At this stage, the type of emergency, the area of coverage, the degree of damage to civilian infrastructure, the number of people located in the endangered area are determined, and the possibility of further escalation is assessed.

The large amount of information that needs to be received and analyzed in emergencies makes it difficult for decision makers to process. They are unable to assess all the indicators and consequences of the situation and make a quality decision on humanitarian response in a short time, which can lead to unforeseen and tragic consequences. The use of DSS will help to make a complete and objective analysis of a dynamically changing situation and forecast its development, especially when solving poorly structured problems.

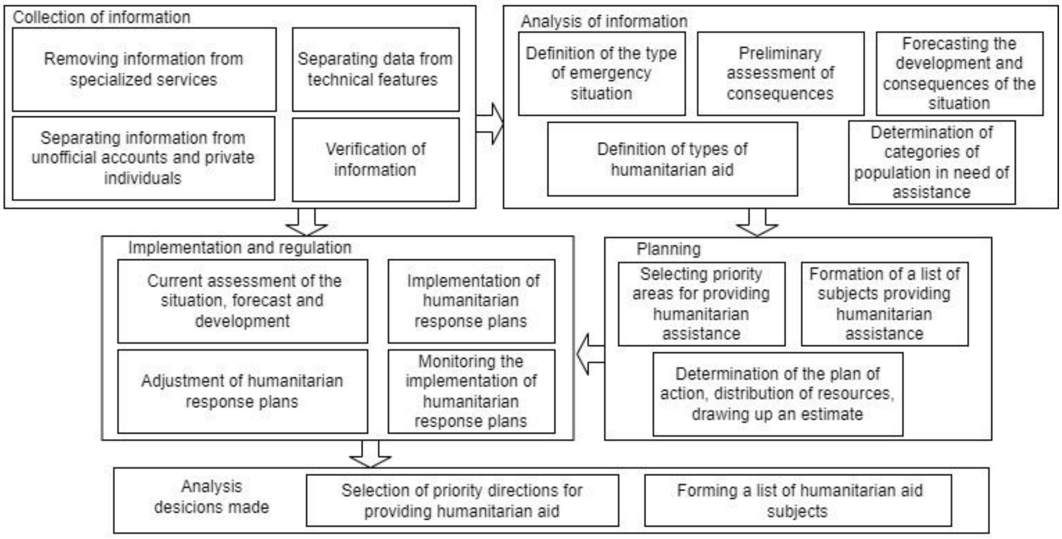

Figure 1: The structure of the decision-making process in humanitarian response.

Taking into account that in most cases the algorithm for solving a problem requiring humanitarian response is uncertain, the use of machine learning methods may be a promising direction. These methods allow to move from direct approaches of algorithmic problem solving to learning in the process of finding a solution.

DSS in humanitarian response should support different ways of representing knowledge about the subject area and solve such problems:

- prompt obtaining of information from various sources, preliminary analysis of data, data cleaning and aggregation;
- interaction with geographic information systems, institutional and other databases and distributed information systems;
- data visualization, including spatial data;
- intellectual analysis of data, building forecasts and dependencies, also in conditions of uncertainty, when information about the situation is insufficient or impossible to obtain;
- storage of previous experience in decision-making in the field of humanitarian response in the form of knowledge-based models;
- assessing the quality of decisions made.

The structural component of the DSS is the Case-Based Reasoning module, which simulates human reasoning and is based on the effective use of existing experience. The module should perform the following functions:

- creation of case models, including parametric and ontological representation;
- identification of the current situation;
- searching for and extracting cases that are most relevant to the current situation;
- adaptation of the obtained solutions to the current situation;
- verification and storage of adapted cases.

A hybrid CBR method should be the basis of such a module, allowing for the search and adaptation of cases that have different representations. Traditional CBR [3] allows representing knowledge about a subject area in the form of a certain description of a situation and its corresponding solution:

$$case = < situation, solution, result >, \tag{1}$$

where *situation* – situation describing a given case; *solution* – a decision made in a given situation; *result* – the result of applying a decision.

The parametric case representation is the most common, as most datasets are fully or partially represented in parametric form. Also, processing such data requires less support and maintenance costs compared to other case representations.

On the other hand, the parametric representation significantly limits the effectiveness of the CBR method in cases where decisions have to be made under conditions of uncertainty. To represent more complex relationships between the concepts of the subject area, it is advisable to use the ontological structure of the case. The ontological representation is an explicit specification of the conceptualization, it allows you to create a model using the concepts with which experts analyze information. To take into account the peculiarities of the subject area, various types of data, quantitative and qualitative characteristics should be operated with. Therefore, two types of case representation should be used for decision support using CBR. A simple parametric representation is sufficient for quantitative data characterizing a situation. In this case, CBR selection can be implemented using one of the modifications of the nearest neighbor method. Therefore, an ontological representation of a case can be used for strategic decision-making, and a parametric representation can be used for operational decision-making.

Different types of search are used for different case representations. For the parametric representation, a proximity measure is found, for example, by the Manhattan or Euclidean metric. For the ontological representation, semantic proximity measures are used, which in turn are divided into lexical proximity and conceptual proximity. In this case, the question arises of the comparability of parametric and semantic proximity measures.

4. Development of CBR method

The features of CBR using an ontology are presented below. The advantage of the ontological approach is a holistic and systematic representation of the subject area, which makes knowledge accessible and allows for its reuse. The ontological approach provides a new level of integration of information from various sources to solve search problems.

An ontology represents the main concepts of a subject area in the form of a hierarchy, relationships between concepts and their attributes, as well as axioms and inference rules.

Each ontology reflects a certain view of the subject area and is designed to solve specific tasks.

The ontological representation of a Case contains a concept to describe it, which in itself contains the concepts Situation and Solution, which describe other concepts that represent the parameters of the case and its solution, respectively. The same concept must be contained in the current situation ontology.

To search for similar cases in the ontological representation, it is necessary to determine the degree of semantic closeness. The complexity of its definition is due to the wide variety of similarity aspects. The presence of axioms and inference rules allows taking into account both the complete coincidence of concepts and the relationship between them. The semantic characteristics of concepts, such as their attributes, relationships with other concepts, and position in the ontological hierarchy, are used as measures of semantic similarity.

The description of the current situation may be incomplete, and then the search by parametric representation will be ineffective. When searching in an ontology, the current situation can be considered as a fuzzy set containing, in addition to the defined concepts, close concepts for which the level of semantic closeness is higher than the specified one.

An approach to determining quantitative estimates of semantic closeness is considered. Formally, an ontology is represented by a tuple:

$$O = (L, C, R, \Lambda, E^C, E^R, A), \tag{2}$$

where L – lexicon: $L = L^C \cup L^R \cup L^\Lambda \cup L^{V\Lambda}$, i. e. a set of terms of concepts (L^C), relations (L^R), attributes (L^Λ), attribute values ($L^{V\Lambda}$); C – a set of concepts, R: $C \times C$ – a set of relations between concepts; Λ: $\mathrm{C} \times L^{V\Lambda}$ – concept attribute set; E^C: $C \times C$ – taxonomic class hierarchy; E^R: $R \times R$ – relations hierarchy; A – a set of axioms.

In the set R, which is the main relationship $\leq^{\mathrm{C}}$ ($\leq^{\mathrm{C}} \in R$), defining the general structure of concepts in the domain, $\leq^{\mathrm{C}}$ is a partial order between concepts such that if $(c_i, c_j) \in C \times C$, $c_i \leq^{\mathrm{C}} c_j$, where c_i – subconcept c_j. In addition to that, c_i is a child in c_j, and c_j is a parent c_i. This relation $\leq^{\mathrm{C}}$ defines a taxonomy in which there is a main root node that has no parent node in the ontology. Any concept without children is called a leaf node. The shortest path between this root node and any concept $c_i \in C$ – is the depth of the concept in the hierarchy denoted by $\rho(c_i)$.

Let's describe the set of all attributes L^Λ, where

$$L^\Lambda = \left\{\begin{array}{c}\text{description of the situation, source characteristics,}\\ \text{risk level, probability of deterioration,}\\ \text{associated hazards, duration in time, area, population density,}\\ \text{density of infrastructure facilities,}\\ \text{percentage of affected houses, water quality,}\\ \text{accessibility of water, availability of water}\end{array}\right\}.$$

This set of L^Λ a attributes can be divided into three subsets corresponding to categories or classes of attributes:

$$L^\Lambda = L^\Lambda_{\text{substantial}} \cup L^\Lambda_{\text{territorial}} \cup L^\Lambda_{\text{resultant}}.$$

Each of the categories can be represented as follows:

$$L^\Lambda_{\text{substantial}} = \left\{\begin{array}{c}\text{source characteristic, risk level, probability of deterioration,}\\ \text{associated threats, duration in time}\end{array}\right\};$$

$$L^{\Lambda}_{territorial} = \{\text{area, population density, density of infrastructure facilities}\};$$

$$L^{\Lambda}_{\text{resultant}} = \begin{Bmatrix} \text{percentage of affected houses, water quality,} \\ \text{water availability} \end{Bmatrix}.$$

The weight associated with an attribute for a concept is represented by $\omega(a, c)$. It represents the importance of the attribute for defining and describing the concept.

Axioms are the basic building blocks for fixing the semantic interpretation of concepts and relations of an ontology. There are general-purpose axioms and domain-specific axioms. The former – axiom schemes – represent the classical properties of concepts or relations.

For example, in order to provide a taxonomy of concepts/relations (tree or lattice), an IS-A relation between two concepts or two relations should be fixed (called the subsumption property). There is also a disjunction between two concepts, the power of the relation, and the algebraic properties of the relation (symmetry, reflexivity, transitivity, etc.). The axioms of a subject area are completely specific to the subject area and often have a preceding part and a consequent part with formal semantics that corresponds to the rule "if the preceding part is true, then the consequent part is true".

The process of searching for a case similar to the current situation, containing previous experience of disasters and response to them, is proposed to be carried out as ontology development, which is based on the reuse of existing ontological resources, studying their parameters and formalizing knowledge.

The development process consists of three stages:

1. Selecting the ontology that best suits the current situation and adopting it as the main ontology for solving the problem.
2. Adaptation and development of the main ontology to eliminate the imperfection of the current situation in terms of territorial, essential and effective attributes.
3. Enrichment of the adapted ontology with new knowledge based on existing taxonomies, thesauri and knowledge gained from previous experience using methods of alignment and fusion of cases represented as ontologies.

The first step in CBR is to select the ontological case that is closest to the current situation. The current situation is represented by a set of parameters, each of which has a quantitative or qualitative value. It is necessary to determine the shortest distance by comparing the parameters of the situation with the concepts of existing ontological cases, and the quantitative characteristics of the parameters with the values of their instances.

With respect to $R(X, Y)$, X is a domain – set, for which it is admissible to use the relation, Y – range – is the range of permissible values of the relation. For example, for the relation "carries in itself" the multiplicity of threats is domain, and the multiplicity of consequences – is range. Let us define the proximity measures of ontological terms using the function $\rho(x, y) \in [0, 1]$.

The closeness of two concepts will be evaluated by the position of the vertices corresponding to these concepts in hierarchical ontological structures, mainly in the taxonomic hierarchy. As a measure of closeness, we will use the length of the shortest path –

the number of edges between the two corresponding vertices of the taxonomy. The shorter the path length between the nodes, the closer they are:

$$\rho(c_1, c_2) = \log \frac{2\Delta}{d(c_1, c_2)}, \tag{3}$$

where Δ – is the depth of the tree, $d(c_1, c_2)$ – is the length of the shortest path between the vertices.

The second stage involves the adaptation and development of the selected ontology closest to the current situation to eliminate uncertainty and to represent essential, territorial and performance parameters by adding missing dimensions.

Suppose S_q and S_t – are fragments of situations q and t, respectively. Then we define the proximity criterion φ of these semantic schemes as follows:

$$\varphi^p(S_q, S_t) = S_q \approx S_t, \tag{4}$$
$$\varphi^p(S_q, S_t) \in D, D = [0,1],$$

where the symbol $\approx$ stands for the proximity operation, and D – is the set of values of the proximity criterion. If $\varphi^p(S_q, S_t) = 1$, there is complete proximity, if $\varphi^p(S_q, S_t) = 0$, there is no proximity. To search for "proximity situations" at the first stage we use the nearest neighbor method [3].

Another way to develop inverse ontology is to compare different ontologies with different conceptualizations of the same subject area with different lexicons of terms used and in different ways of conceptualization of its representation. To compare ontologies it is necessary to define cross-ontological measures of conceptual proximity.

Representation of the ontology O_1 on the ontology O_2 means trying to find for each of the concepts in the ontology O_1 a similar concept in the ontology O_2, i.e. the task of finding the best candidates for ontology matching arises. The taxonomies of the two ontologies can be linked through «multiplicity» – vertices corresponding to equivalent concepts.

The parameters of the measure – the length of the shortest path between two vertices corresponding to the compared concepts, and the general specificity of vertices are calculated taking into account the introduced multiplicity. The nearest common parent (LCS) for the compared concepts from different ontologies O_1 and O_2 and the nearest common parent of the first element of the compared pair and the vertex-multiplicity:

$$LCS(c_{1i}, c_{2j}) = LCS(c_{1i}, Multiplicity).$$

The path between two compared nodes passes through node-multiplicity and through two ontologies with different taxonomy depths. Part of the path length in the secondary ontology is "scaled" by the path length in the primary ontology:

$$d(c_{1i}, c_{2j}) = d(c_{1i}, \mathrm{c}) + \frac{2\Delta_1 - 1}{2\Delta_2 - 1} d(c_{2j}, Multiplicity) - 1,$$

where Δ_1 and Δ_2 – depth of relevant taxonomies, $d(c_{1i}, Multiplicity)$ and $d(c_{2j}, Multiplicity)$ – lengths of paths from each vertex to vertex-multiplicity, subtract 1 since vertex-multiplicity is counted twice.

To measure proximity, the semantic distance $D\sigma$ [18], which is the inverse of semantic proximity, is used: the larger the semantic distance, the smaller the semantic proximity. The notion of general specificity of two vertices is introduced

$$Sc(c_1, c_2) = \Delta_1 - \Delta(LCS(c_1, c_2)),$$

where Δ – taxonomic tree depth. The smaller the specificity of two nodes, the greater their closeness. Semantic distance is a function of two parameters – the length of the shortest path between General specificity Sc/C_{sp} of two vertices and semantic distance $D\sigma$ at presence of one vertex-multiplicity are calculated by formulas [18]:

$$Sc(c_{1i}, c_{2j}) = \Delta_1 - \Delta(LCS(c_{1i}, Multiplicity)),$$

$$D\sigma(c_{1i}, c_{2j}) = \log((d(c_{1i}, c_{2j}) - 1)^{\alpha}(Sc(c_{1i}, c_{2j})^{\beta} + \varsigma).$$

where $\alpha > 0, \beta > 0; \varsigma \geq 1$ – constant (provides nonlinearity and positivity $D\sigma$), $d(c_1, c_2)$ – length of the shortest path between vertices. Two ontologies can have many pairs of equivalent vertices forming vertex-multiplicity. For multiple multiplicity linking two ontologies:

$$D\sigma(c_{1i}, c_{2j}) = \min_{m=1,2,\dots,k}\{D\sigma_m(c_{1i}, c_{2j})\}, \quad (5)$$

where k – number of vertices-multiplicity. Thus, the semantic distance between two compared vertices (concepts in different ontologies) is defined as the minimum of the set of distances over all vertices-multiplicity.

At the third stage, the adapted technology is enriched with new knowledge. Conceptual enrichment consists of extracting concepts from separately existing ontological cases, ontological resources, to add them to the main ontology. The enrichment process includes two stages [19].

At the first stage, candidate ontologies are identified: to identify suitable ontological resources for enriching the core ontology, the ontology proximity score is calculated between the candidate ontology and the core ontology.

Let us consider methods for measuring the proximity between ontologies at two levels, verbal and conceptual. At the verbal level, the lexicons of the two ontologies are compared; at the conceptual level, the taxonomies of concepts and other relations of the two ontologies are compared. A lexicon refers to the set of terms of concepts, relations and attributes of an ontology:

$$L = L^C \cup L^R \cup L^{\Lambda}.$$

Lexicon concepts (relations) are related through the ontology function θ, which puts terms in correspondence with concepts (relations) in the ontology.

The conceptual proximity of ontologies is evaluated from two sides – taxonomy proximity and relation proximity.

To calculate the proximity of taxonomies, we use a set of vertices that contains all the above- and below-lying vertices in the E^C taxonomic hierarchy with respect to a given vertex-concept – semantic cotopy (SC):

$$SC(c_i, E^C) := \{c_j \in C | E^C(c_i, c_j) \vee E^C(c_i, c_j)\}.$$

For multiple concepts:

$$SC(\{c_1, \dots, c_n\}, E^C) := \bigcap_{i:=1,\dots,n} SC(c_i, E^C)\ .$$

If a term l is used in both ontologies O_1 with taxonomies H_1^C and H_2^C, then the taxonomic proximity of ontologies with respect to this term is determined by the formula:

$$\rho(l, O_1, O_2) := \frac{\left|\Theta_1^{-1}\left(SC(\Theta_1(\{l\}), E_1^C)\right) \cap \Theta_2^{-1}\left(SC(\Theta_2(\{l\}), E_2^C)\right)\right|}{\left|\Theta_1^{-1}\left(SC(\Theta_1(\{l\}), E_1^C)\right) \cup \Theta_2^{-1}\left(SC(\Theta_2(\{l\}), E_2^C)\right)\right|}.$$

The more the same terms in the SC of the concepts named by this term in both ontologies, the greater the taxonomic closeness of the ontologies with respect to this term.

If a term exists only in one ontology and is absent in the second ontology, the SC terms of the concept corresponding to term *l*, and all concepts in the second ontology are compared, and the maximum is taken as the taxonomic proximity with respect to this term:

$$\rho'(l, O_1, O_2) \coloneqq \max_{c \in C_2} \frac{\left|\Theta_1^{-1}\left(SC(\Theta_1(\{l\}), E_1^C)\right) \cap \Theta_2^{-1}\left(SC(\Theta_2(\{l\}), E_2^C)\right)\right|}{\left|\Theta_1^{-1}\left(SC(\Theta_1(\{l\}), E_1^C)\right) \cup F\Theta_2^{-1}\left(SC(\Theta_2(\{l\}), E_2^C)\right)\right|}, \tag{6}$$

Such an operation is done for each term in the first ontology, after which the taxonomic proximity for the two ontologies is computed as an average over the lexicon of concepts in the first ontology:

$$\rho_t(O_1, O_2) = \frac{1}{|L_1^C|} \sum_{l_i \in L_1^C} \rho(l, O_1, O_2),$$

where

$$\rho(l, O_1, O_2) = \begin{cases} \rho'(l, O_1, O_2), & \text{if } l \in L_2^C, \\ \rho''(l, O_1, O_2), & \text{if } l \notin L_2^C. \end{cases}$$

The second stage of enrichment involves integration and placement: the selected concepts derived from the extracted mappings of the first stage should be added to the ontological case being enriched in the right place.

The next step is axiomatic enrichment, i.e. enrichment of the ontological case with axioms and rules of logical inference, which allows reasoning using the mechanism of logical inference. Most reasoning uses first-order predicate logic to perform reasoning, and inference is usually performed using forward and backward binding.

5. Experiment

To analyse the application of the proposed method, a prototype module for reasoning on cases with support for the ontological representation of cases was developed. The prototype implements the following functions:

- input and storage of cases in parametric and ontological representation;
- reasoning on parametric cases described in [4] with the storage of a new adapted case;
- reasoning on ontological cases, which includes the stages of selecting the ontology closest to the current situation, adaptation and development of the selected ontology and its enrichment.

The input data for the module are the parameters of the current situation. The output data is a new case obtained as a result of the adaptation and enrichment of the ontology closest to the current situation. The resulting ontology is provided to the expert for further decision-making on whether to store it as a case in the database for future use.

As part of obtaining a data set for the experimental study of the developed method, a classification of threats that lead to the need for a humanitarian response was carried out. In accordance with [1], the following humanitarian assistance clusters were identified:

coordination and management of accommodation facilities for internally displaced persons; food safety and subsistence; water, sanitation and hygiene; housing and non-food items; protection; education; and multipurpose cash assistance. For each cluster, an initial classification of threat types and typical response scenarios have been identified. A fragment of the threat classification for the water, sanitation and hygiene cluster is shown in Table 1.

Table 1
Fragment of the threat classification for water, sanitation and hygiene

Help cluster	Types of threat	Threat	Scenarios
Water, sanitation and hygiene	Technological/ Industrial threats	Emergency state of water supply/drainage systems (WSDS) Exposure of harmful substances to the WSDS Pollution of groundwater and surface water Pollution of drinking water sources	Maintenance and repair works Clean-up activities Water supply to the population Anti-epidemic measures
	Natural threats	Flood Drought Storm Earthquake Fire	Search for additional water sources Water supply to the population Anti-epidemic measures
	Logistical threats	Obstruction of transport routes Destruction of transport routes Destruction of supply chains	Development of additional routes Involvement of new suppliers
	Hostilities/ warfare	Destruction of WSDS Power outages Inability to access centralised WSDS	Evacuation of the population Maintenance and repair work Demining
	Organisational/ political threats	WSDS technical maintenance errors Accumulation of uncollected household waste Lack of sanitary and hygienic control Reduced budget/capacity for WSDS maintenance	Maintenance and repair works Search for additional funds with the involvement of sponsors Anti-epidemic measures

On the basis of the classification and data from [1] and other open sources, fifty ontological representations of cases were developed to reflect the relationship between emergencies and humanitarian assistance scenarios. Examples of ontologies are shown in Figure 2. In addition to hierarchical relationships, the ontologies contain object relationships between concepts, which allows for logical inference.

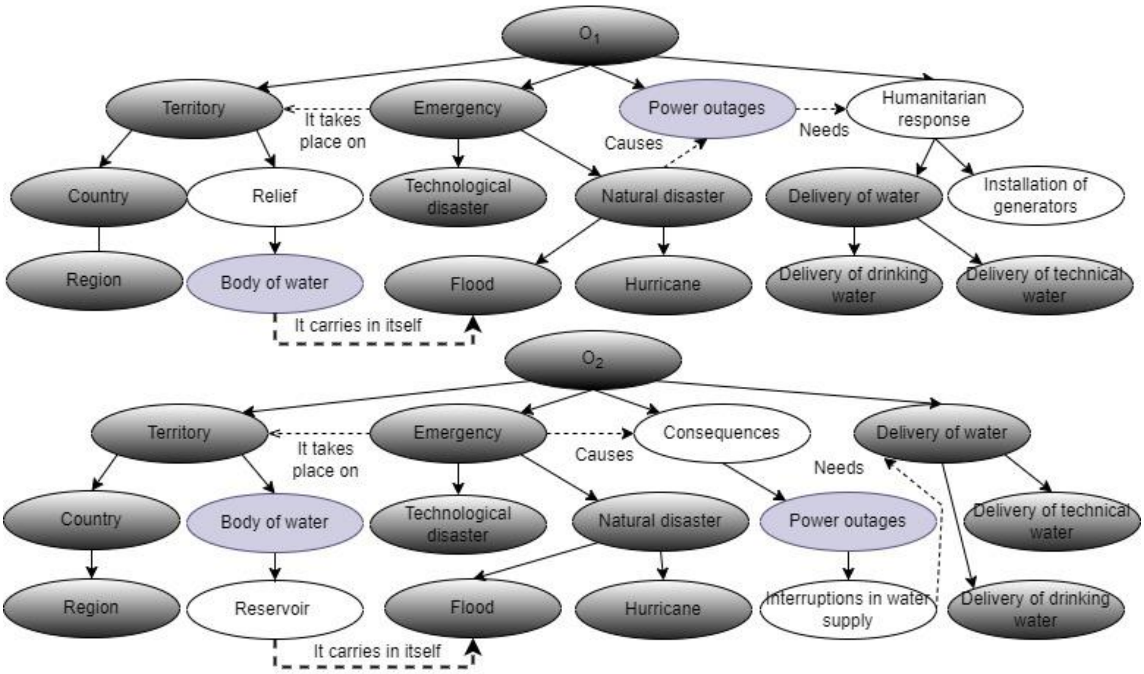

Figure 2: Examples of ontological representation of cases used in the experiment.

Figure 2 illustrates an example of similar ontologies for different situations of this type. For example, in ontology O_1 the concept Territory has a child Relief, because the events took place in a mountainous area, and this concept directly affects the need for humanitarian response. Ontology O_2 was developed for a flat landscape, so the topography did not have a significant impact on the situation, but as in the first case, there were water resources that could cause flooding (the Carries relationship, shown by the dashed line).

A system of inference rules was developed to model the links between threats and possible humanitarian assistance scenarios. For example, the following rules were used to make an evacuation decision:

- IF ((probability_of_attacks ≥ 0,5) AND (volume_of_water_in_the_reservoir > 100 million m2)) THEN flood_risk = HIGH;
- IF ((residential_quarters NEAR the dam) AND (flood_risk = HIGH) AND (population size ≥ 30 thousand)) THEN evacuation_of_population = YES.

Another example is the formation of rules for threats related to the lack of power supply:

- IF ((blackout_time ≥ 6 hours) AND (absence_of_heating ≥ 20 thousand) AND (absence_of_heating = YES) AND (season_variable = WINTER)) THEN installation_of_generators = YES.

6. Results

Let's consider an example of the development of an ontological case that was determined to be the closest to the current situation at the first stage of CBR. Figure 3 shows a fragment of case O_1. In the process of its development, case O_2 In the process of its development, case O_1 with a new branch. The result is the – case Enriched O_1.

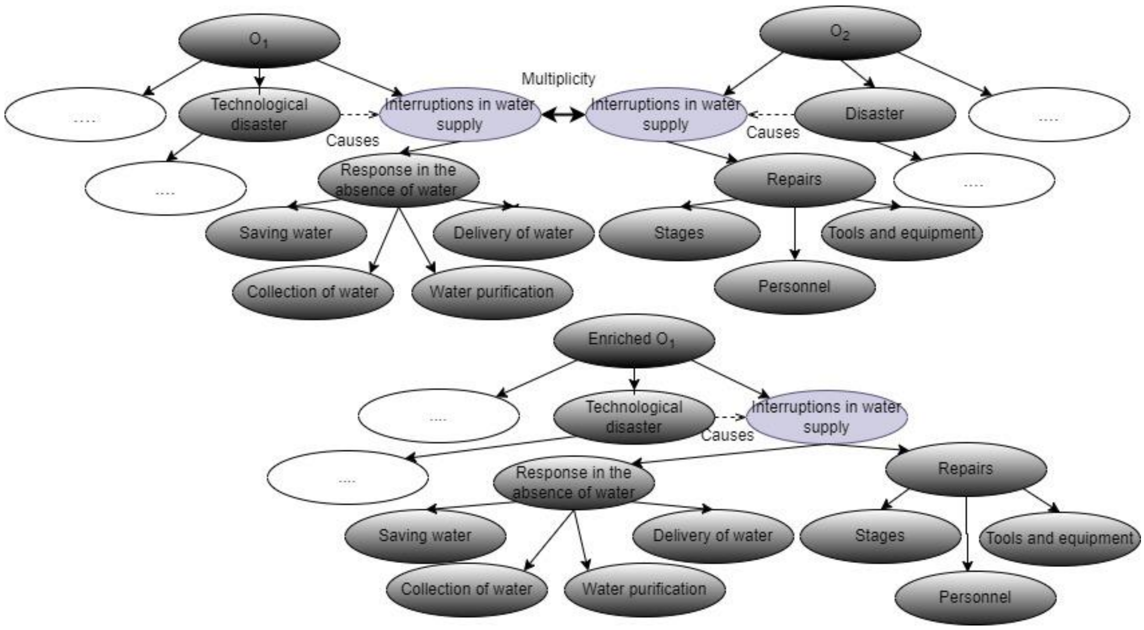

Figure 3: An example of the development of an ontological case by merging multiplicity vertices.

Let's consider the enrichment stage on the example of finding water for the population (the classification from [20] was used to build ontologies). Suppose that the ontologies O_1 and O_2 (Figure 4) correspond to the partially overlapping lexicons L_1 and L_2.

To determine taxonomic proximity ρ'(«water sources», E_1, E_2) by the formula (6):

$$\Theta_1^{-1}\left(SC\left(\Theta_1(\{\text{«water sources»}\}), E_1^C\right)\right) =$$

$$= \{\text{«water sources», «water intake», «groundwater», «surface water»}\};$$

$$\Theta_2^{-1}\left(SC\left(\Theta_2(\{\text{«water sources»}\}), E_2^C\right)\right) =$$

$$= \{\text{«water sources», «groundwater», «surface water», «precipitation»}\}.$$

Consequently, S'(«water sources», E_1^C, E_2^C) $= 1/5$.

For the term «water intake», which is only in the lexicon L_1^C:

$$\Theta_1^{-1}\left(SC\left(\Theta_1(\{\text{ «water intake»}\}), E_1^C\right)\right) =$$

$$= \{\text{«river», «lake», «reservoir», «artesian spring», «rain», «snow»}\}.$$

In the ontology O_2 there is no concept corresponding to «water intake», so the one that will give the best result is taken. In this situation it is «water sources»:

$$\Theta_2^{-1}\left(SC\left(\Theta_2(\{\text{«water sources»}\})\right)\right) = \{\text{«groundwater», «surface water», «precipitation»}\}.$$

Therefore:

$$S''\left(\text{«water intake»}, E_1^C, E_2^C\right) = 1/7.$$

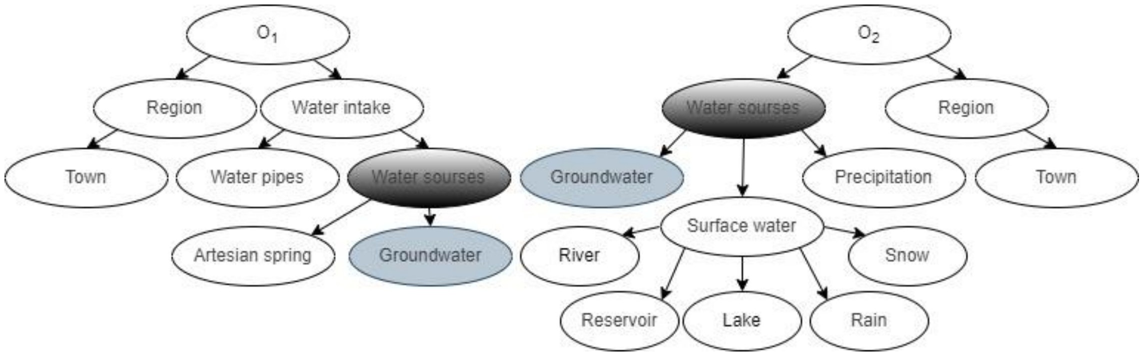

Figure 4: An example of enriching an ontological case.

In other words, when enriching the ontology, we can use the found cases where the lexicons have a partial overlap. The decision is made based on the found coefficients.

In the course of the experiment, we evaluated the classification quality on the initial dataset using the parametric representation of cases described in [4] and the ontological representation. In both cases, the database was initially filled with ten cases. Each subsequent case out of the fifty developed cases was fed as a new situation requiring a decision, after which the cases were searched and adapted using the appropriate CBR method. The resulting solution was compared with the solution contained in the original case, and its quality was assessed.

Figure 5 shows the resulting relationship between the quality of classification and the number of cases in the database when using the parametric representation of cases described in [4] and the extended ontological representation of cases using the proposed adaptation method.

7. Discussions

As can be seen from Table 1, different types of threats lead to similar consequences, for example, both man-made threats and hostilities can lead to disruption of water supply. In this case, similar humanitarian response scenarios can be used. Therefore, the adaptation of previous experience in providing humanitarian assistance to new threats using an ontological approach will allow finding solutions even when the parameters of the current situation are incomplete or if the closest case found only partially reflects the current situation.

As can be seen from Figure 5, in the case of the parametric representation of cases, when the database is filled with ten cases, the classification quality is 36%, and then gradually increases with the database replenishment and reaches 89% when the number of cases is fifty. When using the GBR extended with ontologies, the classification quality increases from 40 to 94 % with the same number of cases. That is, we can conclude that the use of ontologies in the proposed CBR increases the quality of the CBR by an average of 5 %.

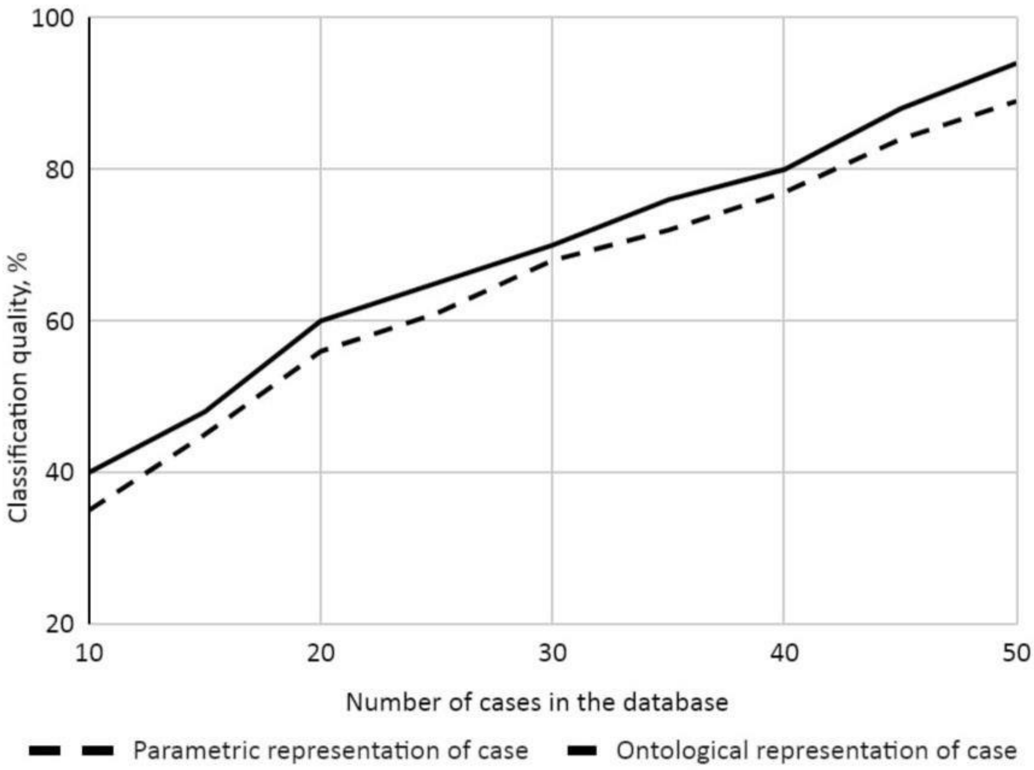

Figure 5: Dependence of the quality of case classification on the number of cases.

Limitations of the proposed method may be determined by insufficient information about the subject area. Therefore, to solve this problem, it is advisable to continuously accumulate experience and develop a general ontological model with gradual modification and expert evaluation.

Further improvement of CBR using ontologies is possible in the following directions:

- introducing additional measures of semantic closeness of ontologies, in particular, taking into account the semantic closeness of concepts;
- development of a system of threat risk indicators and consideration of the semantic correlation between risk indicators and humanitarian response needs;
- development of a common ontology of humanitarian response, determination of procedures for its enrichment and integration;
- expanding the mechanisms of logical inference through the use of fuzzy logic, which will improve the quality of decision-making under conditions of uncertainty.

8. Conclusions

An integrated approach to addressing the challenges of providing assistance will reduce the time and costs of humanitarian response in disaster-affected areas. In the course of researching the stages of decision-making in humanitarian response, the functions of the DSS, which uses previous experience, were identified. The basis of the DSS is the Case-Based Reasoning module, which allows searching for similar situations without first conducting time-consuming stages of knowledge acquisition in the subject area.

The extension of the traditional CBR with an ontological component allows taking into account not only previous experience, but also conceptual and semantic connections between the concepts of the subject area, as well as extending them with rules of logical inference. Additional stages of adaptation and enrichment of ontological cases using semantic proximity measures (1)-(5) allow obtaining an effective solution even in the face of incomplete information about the current situation. Another advantage of the method is the high quality of classification even with a small case database.

The use of adaptable methods and models of knowledge representation at all levels of management will increase the efficiency and timeliness of humanitarian assistance. The proposed modified CBR with an ontological component can be used in the development of DSS for both volunteer organizations and charitable foundations providing humanitarian assistance, as well as for specialized services, government and local authorities.

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